Context-Aware IoT Service Recommendation Methods: A Postprint

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Date: 2019-01-03T00:00:00+00:00

Abstract

With the rapid development and maturation of service computing and Internet of Things (IoT) technologies, a large number of IoT services have emerged on the network. How to efficiently recommend the most suitable IoT services for users based on their real-time context has become one of the key issues urgently requiring solution in the current fields of service computing and IoT. To address this issue, we propose a context-aware IoT service recommendation method. First, a list of IoT services available to the current user is generated based on an improved FolkRank algorithm; subsequently, a user context information model is constructed according to the user' s current key context, and IoT services that best satisfy the user' s current context are filtered from the service list based on this model. Experimental results demonstrate that the proposed context-aware IoT service recommendation method is feasible and effective.

Full Text

Preamble

Vol. 37 No. 3
Application Research of Computers
Accepted Paper

Research on Context-Aware IoT Service Recommendation Methods

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Abstract: With the rapid development and maturation of service computing and Internet of Things (IoT) technology, a vast number of IoT services have emerged on the network. Recommending the most suitable IoT services for users based on their real-time context has become a critical challenge in the fields of service computing and IoT. To address this issue, this paper proposes a context-aware IoT service recommendation method. First, an improved FolkRank algorithm is used to generate a list of IoT services available to the current user. Then, a user context information model is constructed based on the user' s current key context to filter out the IoT services that best satisfy the user' s immediate situation from the service list. Experimental results demonstrate that the proposed context-aware IoT service recommendation method is feasible and effective.

Keywords: Internet of Things; IoT service; context-aware; service recommendation

0 Introduction

The Internet of Things (IoT) represents the third wave of the information industry, following computers and the Internet [1]. Building upon the accumulated achievements of these previous technologies, IoT extends the reach of information acquisition to the perception layer, enabling broader interconnectivity. IoT can autonomously interact with and respond to the physical world to accomplish designated tasks. With the flourishing development of IoT, various cross-industry and cross-domain sensing devices and terminals can rapidly access the network and converge, connecting an increasing number of smart devices [2] that provide users with diverse intelligent services.

IoT services inherit and extend traditional Web services, representing the extension of Web services into the physical world through sensors. An IoT service refers to a service built upon networked smart devices that implement specific applications. IoT service recommendation is the process of extracting massive data generated by smart devices, organizing and analyzing this data, and identifying services that meet user needs from a service pool to push to users within an IoT environment. With the development and proliferation of wireless networks, mobile computing, and smart devices, IoT services have been widely applied across various domains such as smart elderly care, smart cities, and smart agriculture, with an increasing number of users relying on IoT services to manage their work and daily life affairs.

Taking the elderly care domain as an example, traditional approaches require children to accompany elderly parents with medical conditions to handle daily life affairs. However, due to the busy work and life schedules of younger generations, they cannot stay with the elderly for extended periods, resulting in many seniors living alone without timely access to necessary medical, healthcare, and life services, which severely impacts their quality of life. The emergence of IoT and IoT services provides a solid technical foundation for smart home-based elderly care, enabling the timely capture of various data about the elderly through smart devices, inferring their needs through reasoning, and accurately recommending the most suitable IoT services. Consequently, using various IoT services provided by smart devices to improve the quality of home-based elderly care has become feasible.

However, as the number of IoT services surges, the network sees a massive scale of cross-domain available IoT services. Different users possess different smart devices, creating complex relationships among users, IoT services, and smart devices. For users lacking domain knowledge (especially mobility-impaired elderly individuals), manually discovering and selecting IoT services is an extremely difficult task that significantly affects the effectiveness and utilization of IoT services. Therefore, how to efficiently recommend the most appropriate IoT services based on users' current contextual information has become a key issue that urgently needs to be addressed in service computing and IoT.

Currently, research on IoT service recommendation is still in its infancy. Wei et al. [3] proposed an IoT service discovery method based on probabilistic topic models to address the large-scale, heterogeneous, and mobile characteristics of IoT services. Mashal et al. [4] introduced the concept of IoT service recommendation systems through a formal model and proposed a graph-based recommendation system for IoT architectures. Forestiero et al. [5] proposed a multi-agent distributed recommendation algorithm for IoT environments using decentralized self-organizing strategies. Mashal et al. [6] proposed a hypergraph model for service recommendation in IoT environments, where each hyperedge connects users, services, and smart devices, and subsequently conducted in-depth studies on the usefulness of traditional recommendation methods and their hybrid approaches for IoT service recommendation. Saleem et al. [7] argued that IoT service recommendation could be achieved by utilizing data generated from various IoT applications and leveraging Social IoT (SIoT), proposing a concept for service recommendation across multiple IoT applications through exemplary application scenarios. Wang et al. [8] studied IoT service recommendation strategies based on user attribute similarity and attribute correlation between users and device services, employing a tensor linear regression model to address the cold-start problem in service recommendation. He et al. [9] studied the problem of dynamically updating QoS attribute vectors for optimal service selection in WoT devices, proposing a service evaluation and selection architecture based on dynamic QoS updates.

While these studies have achieved certain results in IoT service discovery and recommendation, promoting the development of IoT service applications, they primarily focus on functional and performance-based selection or recommendation methods for IoT services, lacking in-depth research on the impact of user contextual information on IoT service recommendation. In fact, the operation of IoT services depends on specific physical environments, such as user location, network conditions, and smart devices. Therefore, when recommending IoT services to users, it is essential to consider real-time contextual information and recommend the most suitable services based on their current situation to improve recommendation success rates. To address these limitations, this paper proposes a context-aware IoT service recommendation method that first generates a list of available IoT services for the current user based on the FolkRank algorithm, then constructs a user context information model according to the user's current key context to filter out the services that best match their immediate situation. Experimental results demonstrate that incorporating contextual information can improve the success rate of IoT service recommendation.

1 IoT Service Recommendation Problem Modeling

Compared with traditional Web services, IoT services involve not only user and service domains but also a smart device domain. Therefore, IoT service recommendation is a three-dimensional problem involving user, IoT service, and smart device domains [10]. Modeling this problem thus transforms it into a mathematical representation of these three spaces and their relationships.

Currently, numerous IoT services, smart devices, and large-scale personalized users exist in IoT environments, constituting the service space, smart device space, and user space in IoT service recommendation. Complex relationships exist among objects in these three spaces: users have ownership relationships with smart devices, potential subscription relationships with IoT services, and services have compatibility relationships with smart devices. Meanwhile, the massive number of objects within each space creates numerous information silos. These complex relationships and information silos make it difficult for users to quickly and accurately discover services that meet their needs. To enable rapid IoT service discovery, this paper first employs a tripartite undirected graph to describe users, services, smart devices, and their relationships, then formalizes the IoT service recommendation problem as a graph-based link prediction problem.

Taking the smart elderly care domain as an example (as shown in [Figure 1: see original paper]), consider a community elderly care center with users u_1, u_2, and u_3, deployed IoT services including medical service s_1, location service s_2, and alarm service s_3, and smart devices including smartwatch o_1, smart mattress o_2, and smoke alarm o_3. User u_1 uses medical and location services from the smartwatch and medical and alarm services from the smart mattress; user u_2 uses location service from the smartwatch, medical service from the smart mattress, and alarm service from the smoke alarm; user u_3 uses medical service from the smartwatch and medical and alarm services from the smart mattress. The server infers user needs through the relationships among objects in the three spaces and pushes services to users in a timely and accurate manner. The relationships among users, IoT services, and smart devices are illustrated in [Figure 1: see original paper].

For the IoT service recommendation problem, let $U = \{u_1, u_2, ..., u_m\}$ denote the set of m users, $S = \{s_1, s_2, ..., s_p\}$ denote the set of p IoT services, and $O = \{o_1, o_2, ..., o_n\}$ denote the set of n smart devices. Using these three spaces' objects as vertices and relationships among users u_m, services s_p, and smart devices o_n as edges, we construct a tripartite relationship graph among the three spaces' objects.

This paper defines the IoT service recommendation model as a quadruple: $F = (U, S, O, Y)$, where $Y \subseteq \{u \times s \times o; u \in U, s \in S, o \in O\}$ represents the ternary relationships among objects in the U, S, and O spaces. The ternary relationships in the IoT service recommendation model can be represented through the user-device matrix $M(U, O)$, user-service matrix $M(U, S)$, and service-device matrix $M(S, O)$. Based on these three two-dimensional matrices, we can transform the IoT service instance graph into a tripartite undirected graph and establish its adjacency matrix. The main steps for constructing the tripartite undirected graph are:

a) Construct the user-device matrix $M(U, O)$. The relationship between users and smart devices is represented by an $m \times n$ two-dimensional matrix, where rows represent users and columns represent smart devices. The cell value $M_{u,o}$ indicates whether user u has used services provided by smart device o; $M_{u,o} = 1$ means the user owns the device, while $M_{u,o} = 0$ indicates no ownership relationship. The $M(U, O)$ constructed from [Figure 1: see original paper] is shown in equation (1).

b) Construct the user-service matrix $M(U, S)$. The relationship between users and services is represented by an $m \times p$ two-dimensional matrix, where rows represent users and columns represent services. The cell value $M_{u,s}$ indicates the number of times user u has used service s. The $M(U, S)$ constructed from [Figure 1: see original paper] is shown in equation (2).

c) Construct the service-device matrix $M(S, O)$. The relationship between services and smart devices is represented by a $p \times n$ two-dimensional matrix, where rows represent services and columns represent smart devices. The cell value $M_{s,o}$ indicates the number of users who have used service s on smart device o. The $M(S, O)$ constructed from [Figure 1: see original paper] is shown in equation (3).

d) Build the tripartite undirected graph for IoT service recommendation. Based on the three two-dimensional matrices above, we merge edges with non-zero pairwise relationships and represent them with a single edge, where the edge weight corresponds to the value in the three matrices. Through this merging process, we obtain the tripartite undirected graph $G = (V, E)$ for IoT service recommendation, where the vertex set V consists of objects from the user, IoT service, and smart device spaces, i.e., $V = U \cup S \cup O$. The edge set E consists of edges representing relationships among user-device, user-service, and service-device pairs, i.e., $E = \{\{u, o\}, \{u, s\}, \{s, o\} | (u, s, o) \in Y\}$.

Using [Figure 1: see original paper] as an example, the constructed tripartite undirected graph is shown in [Figure 2: see original paper].

The adjacency matrix A corresponding to the tripartite undirected graph G is shown in equation (4). The adjacency matrix A is highly sparse, with three local matrices O_{UU}, O_{SS}, and O_{OO} being entirely zero, and M_{UO}, M_{US}, M_{SO} being transposes of M_{OU}, M_{SU}, M_{OS}, respectively. Therefore, when describing a tripartite undirected graph G, only these three matrices need to be stored.

The IoT service recommendation problem involves, in an IoT environment, screening IoT services from the service set that can satisfy user needs and have the necessary runtime environment (smart devices) based on the relationships among users, IoT services, and smart devices described by the tripartite undirected graph G, and recommending them to users. To enable rapid service screening, this paper converts the tripartite undirected graph G into an adjacency matrix and uses the FolkRank algorithm to quickly generate a recommendation list, then applies a contextual post-filtering approach to achieve context-aware IoT service recommendation.

2 Context-Aware IoT Service Recommendation Method

IoT is a highly heterogeneous network containing numerous types of smart devices, massive IoT services, and large numbers of users with personalized needs. IoT service recommendation involves three spaces with complex relationships among their objects. Traditional recommendation methods primarily focus on two-dimensional spaces and cannot effectively solve context-aware IoT service recommendation problems.

Currently, the FolkRank algorithm [11,12] is a high-performance ranking algorithm commonly used for recommendation problems in social tagging systems comprising users, tags, and resources. Through in-depth analysis, this paper finds that the FolkRank algorithm can quickly capture the relationships among users, IoT services, and smart devices in IoT service recommendation problems, effectively alleviate sparsity issues, and is well-suited for IoT service recommendation.

Furthermore, extensive research demonstrates that contextual information can reflect user preferences in specific situations, and incorporating contextual information can provide more accurate and intention-aligned services. IoT service recommendation involves many key contextual factors such as time, location, and weather, which can effectively improve recommendation effectiveness. Traditional recommendation algorithms like FolkRank do not consider contextual information during problem solving and cannot adequately address IoT service recommendation. To improve the efficiency and effectiveness of IoT service recommendation, this paper first uses the FolkRank algorithm to generate a candidate IoT service list, then constructs a user context information model to filter out the services that best match the user’ s current situation.

The main computational process of the context-aware IoT service recommendation method is shown in [Figure 3: see original paper]. First, the FolkRank algorithm generates a service recommendation list for each user. Then, the recommendation list is adjusted based on the user’ s real-time contextual information. Finally, the IoT services that best satisfy the user’ s context are recommended to the current user.

2.1 FolkRank Algorithm

The FolkRank algorithm is typically applied to social tagging systems composed of users, tags, and resources. Its main computational flow involves: initializing the adjacency matrix, preference vector, and weight vector based on collected data; iteratively computing the final weight vector through differentiated methods; and selecting the Top-N items from the recommendation list for the user. When applying the FolkRank algorithm to IoT service recommendation, IoT services are treated as tags in the system and smart devices as resources. The FolkRank algorithm employs PageRank' s random surfer model for ranking computation.

The iterative calculation formula for the weight vector w in the FolkRank algorithm is shown in equation (5), where w_i is the node weight value at iteration i, A is the adjacency matrix, v is the preference vector, and d is a constant ($d \in [0, 1]$) that determines the influence degree of v.

The FolkRank algorithm computes the weight vector w in two scenarios: one without considering the preference vector v (i.e., $d = 1$), yielding $w_{i+1} = Aw_i$; and another considering the preference vector v (i.e., $d < 1$), yielding $w_{i+1} = dAw_i + (1 - d)v$. If the FolkRank algorithm only considers the case where $d < 1$, the overall structure of the undirected graph weakens the influence of the preference vector. Therefore, a differentiated approach is used to set the final weight vector as $w = w^{(d<1)} - w^{(d=1)}$, thereby reasonably concentrating the ranking on the nodes defined by the preference vector.

2.2 User Context Model

In many application scenarios, relying solely on the relationships among users, services, and smart devices cannot effectively achieve accurate IoT service recommendation. In fact, the same user requires different IoT services when in different contexts. Without considering contextual information, the accuracy of IoT service recommendation will be significantly impacted. Therefore, incorporating context awareness into the recommendation method is essential.

During IoT service recommendation, user context information primarily includes location, lifestyle, social relationships, environmental conditions (temperature, humidity, traffic status, etc.), and device capabilities. This paper refers to this information as user context information. When constructing the user context information model, we first categorize contextual information by grouping information from the same domain type together. Formally, the user context model is defined as a z-tuple consisting of z different context types: $UC = \{C_1, C_2, \dots, C_z\}$, where $C_i (i \in 1 \dots z)$ represents a context type (e.g., time, location, or temperature). The primary objective of this method is to analyze interaction information among users, services, and smart devices along with event context information, rank services according to context matching degree, and select for current user u the IoT service s that best satisfies their current context UC.

Currently, commonly used contextual post-filtering methods include the linear weighting method and direct filtering method proposed by Panniello et al. [13]. Given the characteristics of IoT service recommendation problems, this paper adopts the linear weighting contextual post-filtering method, which linearly combines the probability of association between services and user real-time context with the generated list to adjust the ranking of candidate IoT services. The top-ranked services are then recommended to the current user. The context-aware IoT service recommendation method is described in Algorithm 1.

Algorithm 1 Context-aware IoT services recommendation algorithm
Input: Quadruple dataset, a given user u, a given context c
Output: The set of recommended services $Rating_k(u, o, s)$

1. Initialize the adjacency matrix A, randomly chosen vector w_0 and vector w_1
2. Compute the preference vector v
3. **while** $i \leq num$ **do**
4. Compute the final weight vector
5. Compute $Rating(u, o, s)$ according to w
6. Compute $P_k(i, j)$ according to formula (6)

Where $P_k(i, j)$ is the contextual probability of a given user in a given context, calculated as shown in equation (6). The i-th user uses the j-th service in context k, $neighbor_{max}$ is the total number of all neighbors of user i based on user similarity information, and $neighbor_{min}$ is the number of neighbors of user i who use the same service j according to specific context k.

The calculation of $neighbor_{max}$ proceeds in three steps:
a) Preprocess the user-service matrix $M(U, S)$. Since data values in $M(U, S)$ vary significantly, normalization is required to ensure values fall within $[0, 1]$ for subsequent calculations.
b) Calculate similarity between users. First, obtain the set of services commonly used by users a and b, denoted as I_{ab}. Then compute the similarity $sim(a, b)$ between users a and b using the Pearson correlation coefficient, as shown in equation (7), where $Q_{a,c}$ is the number of times user a uses service c, and $\bar{Q}_a$ and $\bar{Q}_b$ are the average service usage counts for users a and b, respectively.
c) Use the KNN algorithm to obtain neighbors for a given user.

The calculation of $neighbor_{min}$ proceeds in two steps: First, obtain the user-service matrix $C(U, S)$ under similar contexts. Then, select users who share more than L services with the given user as neighbors.

3 Experimental Results and Analysis

Extensive simulation experiments were conducted to verify the feasibility and effectiveness of the proposed method. Since IoT services are still in the early stages of development, publicly recognized datasets are lacking in the research field. To validate the feasibility and effectiveness of our approach, we used the dataset from the IJCAI-18 Alimama International Advertising Algorithm Competition to simulate an IoT system. The dataset is divided into training and test sets, both containing four types of data: user information, advertisement product information, shop information, and context information. The dataset includes numerous attributes about users, advertisement products, shops, and contexts. We extracted only the most fundamental information to form a basic data table, as shown in . When applying this dataset to our simulation experiments, the following mappings were made: IoT service information was treated as advertisement product information, smart device information as shop information, and context information as context data. To verify the effectiveness of the context-aware IoT service recommendation method, we divided the training set into two categories: one without context information (including only user, service, and device IDs) and another with context information (including user, service, and device IDs along with service usage time and location).

Table 1 Basic data table

user_id	object_id	service_id	context_timestamp	context_location
User ID	Smart device ID	Service ID	Service usage time	Service usage location

To evaluate algorithm performance, we adopted the classic precision and recall metrics. Precision measures the correctness of recommendation results, equal to the number of correctly recommended services divided by the total number of recommended services, as shown in equation (8). Recall measures the completeness of recommendation results, equal to the number of correctly recommended services divided by the number of relevant services, as shown in equation (9), where S_u^t represents the top t recommended services and S_u is the set of relevant services for user $u \in U$.

The experimental environment was a laptop with the following configuration: OS: Windows 7; CPU: Intel(R) CoreTM i3, 2.30 GHz; Memory: 4.00 GB. All algorithms were implemented in Python 3.5. To verify the feasibility and effectiveness of our method, we conducted comparative experiments with the FolkRank algorithm and item-based collaborative filtering algorithm. The results are shown in [Figure 4: see original paper], where the horizontal axis represents recall and the vertical axis represents precision.

[Figure 4: see original paper] shows that our algorithm outperforms both FolkRank and item-based collaborative filtering in terms of precision and recall. This demonstrates that IoT characteristics and user contextual information significantly impact recommendation performance, and our algorithm is more suitable for IoT service recommendation, improving both recommendation accuracy and user satisfaction.

We also conducted simulation experiments on the impact of candidate IoT service scale on algorithm precision and recall. In these experiments, we varied the number of candidate services and calculated the corresponding precision and recall values. The results are shown in [Figure 5: see original paper] and [Figure 6: see original paper].

[Figure 5: see original paper] shows the relationship between precision and the number of candidate services. Both algorithms' precision decreases as the number of candidate services increases, but our algorithm achieves 7% higher precision compared to FolkRank. [Figure 6: see original paper] shows the relationship between recall and the number of candidate services. Both algorithms' recall increases with the number of candidate services, but our algorithm achieves 13% higher recall compared to FolkRank. These improvements demonstrate that our algorithm, which reasonably incorporates contextual information, delivers higher recommendation quality and proves its greater feasibility and effectiveness compared to FolkRank.

4 Conclusion

IoT will accelerate information explosion, making it impossible for users to quickly select services that meet their needs. IoT recommendation systems represent the most effective solution to this problem and play a crucial role in IoT popularization. This paper proposes a context-aware IoT service recommendation method that incorporates contextual information into IoT service recommendation using a linear weighting contextual post-filtering approach. Experimental results show that this method improves both precision and recall. In the future, every entity will be assigned an IP address, providing access to more data sources. Researchers can describe contexts from more dimensions to provide better service experiences, truly integrating services with contexts to deliver more efficient and accurate recommendations.

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Note: Figure translations are in progress. See original paper for figures.